Original Research Paper

Evaluation of Surface Drag Interval in the Variable Situations for Modeling of Non-Linear Systems

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Abstract: Tools applied in different fields of engineering are artificial neural networks to model non-linear systems which are efficient and useful. Artificial neural networks consist of input and output layers with one or more hidden layers between them. In fact, one or more processing elements or neurons are used in each layer. Input layer neurons are the independent variables studied and output layer neurons are its dependent variables. The artificial nervous system tries to achieve the desired output by applying weight to the inputs and complaining of an activation function. In this study, artificial neural networks were used so as to estimate the unstable drainage distance in an area located in the northeast of Ahvaz with a variety of soil characteristics and drainage distance. Depth of impermeable layer, special yield, height of water table in the middle of the distance between drains in two time stages and hydraulic conductivity are Input layer neurons applied. There was a discharge distance in the output layer of neurons. The network designed consisted of a hidden layer with four neurons. The distance of the drains was in a proper agreement with the real values estimated by this method and was more accurate than other methods.

Keywords: Hidden Layer, Elements, Soil Characteristics, Input Layer Neurons, Output Layer

Introduction

The ever-increasing population of the world increases the human being's need to agricultural crops. Therefore, paying attention to the agriculture is essential (Häggblom *et al*., 2019). Paying attention to this subject without considering irrigation and optimal use of water resources will not be possible. Each irrigation plan will be successful if in the plan the soil drain issue is considered. In the other words, irrigation and drainage are interdependent. Generally, drainage means remove of excess water and solute from the soil. Lack of appropriate drainage leads to water logging and soil salinity (Qian *et al*., 2021).

In a country like Iran, that in its most parts precipitation is low and evaporation and transpiration is high, we are faced to the problem of salt accumulation in the soils and that such salts should be leached and remove from the plant root access. Otherwise many of

the agricultural lands will become out of reach. In order that the subsurface drains work well, they should be well designed (French *et al*., 1992).

Since the real water flow in the soil towards the subsurface drains is unsteady, such conditions should be considered for appropriate designing of drains. For this purpose, it is possible to act in several methods:

A. Using the equations extracted for unsteady flow of drains like the Glover-Dumm, Van-Schilfgaarde, Bower and Van - Schilfgaarde and Hamed equations The above equations are theoretically extracted employing the physical hypotheses

B. Using the differential equations governing the unsteady flow of subsurface drains which have their own complexities and make possible to simulate fluctuations of the water table that the most famous equation is Boussinesq's equation

Practically prediction of drains based on theoretical relations is accompanied by errors. Evidently if the computed drain spacing is more than what it should be, the water table will go higher than its permitted limit and causes decreased yield (Golmohammadi *et al.*, 2009). On the other hand, if drain spacing is computed less than what it should be, the project being economic is questioned. Regarding the complex behavior of water unsteady flow in the soil, this behavior cannot be expressed by a precise mathematical equation and through a theory and based on which compute the drain spacing (Jain *et al.*, 1999).

In such conditions, the artificial neural networks will prove very beneficial since such networks, do not need to a mathematical relation for the complex phenomenon that they investigate (Kumar *et al.*, 2002). Generally, neural networks are an effective tool for modeling the nonlinear systems. Each artificial neural network includes an input layer, an output layer and one or more hidden layers sandwiched between the aforesaid layers. In each layer there are one or several process elements or neurons which all together act similar to a biological neural network. Artificial neural network following receiving input, attempts to change them to a desirable output. To do so, it gives weight to the input and employs an activation function (French *et al.*, 1992).

This is called network training Thereafter, the neural network model tests itself and finally the model is certified (Rogers and Dowla, 1994). During the last decade, artificial neural networks have been used in various fields. In the field of water engineering the following cases can be pointed out.

French *et al.* (1992), for forecasting rain in location and time, (Rogers and Dowla, 1994), optimization of groundwater, (Shukla *et al.*, 1996), designing of drains at the unsteady state, (Yang *et al.*, 2013) lands drainage engineering, , forecasting rivers water levels, (Jain *et al.*, 1999), predicting inflow water to reservoirs and finally (Kumar *et al.*, 2002) who estimated evaporation and transpiration using artificial neural networks (Qian *et al.*, 2021; French *et al.*, 1992; Golmohammadi *et al.*, 2009; Jain *et al.*, 1999; Kumar *et al.*, 2002).

Young in his studies using the artificial neural networks simulated the relation between the water table depth in the middle of drains and their outflow and designed drains using this simulation. Obtained results had good precision and are even more exact compared with results of the older models like DRAINMOD (Rogers and Dowla, 1994).

Materials and Methods

In this study, drain spacing will be computed through the method of artificial neural networks for a region located in the southeast of lands of the Ramin Higher Educational and Research Complex (affiliated with the Shahid Chamran University of Ahwaz, Iran) at 40 k north east of Ahwaz, Iran towards Shushtar was selected. Part of this farm with the surface area of 11ha having subsurface drains and is composed of three A, B and C sections. Distance between drain to impermeable layer was considered. Characteristics of these three sections are summarized in Table 1. These values are as average.

Hydraulic conductivity was measured using the auger method and using Ernest's equation. The whole research farm for the third consecutive year following establishment of drain system was under cultivation of wheat. These data are for third year.

Therefore, recommendation of FAO regarding condition for establishment of soil stabilization during tests was observed. Each of the above sections from the viewpoint of number and location of inspection hole are similar.

Such that 6 holes are located at the two sides of the drain like at intervals of one fourth, half and three fourth of the drain length in the middle of the interval between the drains. The auger hole method is a standard method for measuring of hydraulic conductivity. Using the information provided by the present meteorology station, mean annual rainfall of the region is 241.4 mm and annual evaporation is 3721 mm, the maximum of which is relevant to July and is equal to 406.7 mm. In such warm and arid regions like Ahwas, Iran heavy irrigation is performed. As a result, in a short period of time, a high volume of water enters the soil and causes rise of the water table. Fall of water table in the middle of interval between the drains relative to drain balances from the height h0 to h needs a time equal to t.

In the conventional methods for computing the drain spacing in unsteady conditions, in addition to the above information (t, h_0, h), the soil hydraulic conductivity (k), specific yield (p) and distance of drains to the confiding layer (d) are needed. In the understudy region data of Table 2 has been collected. The number of irrigation events was more than 3, but the measurements were done for 3 of them.

The aim of this study is that employing the collected data, calculated the drain spacing using the artificial neural networks. The procedure is explained below.

Using the artificial neural networks for determining the drain spacing.

When a variable is dependent on several variables such that their relations cannot be exactly analyzed through a mathematical equation and/or it is not possible to establish via regression a good correlation amongst them, the artificial neural networks can be used.

The structure of these networks resembles the biological neural networks. In the artificial networks, many computations are performed on the independent variables so that the desirable value of the dependent variable can be obtained. Artificial neural networks are composed of some

neurons which are placed alongside each other as a layer. The networks is composed of at least two layers (an input and an output layers) but several hidden layers can be sandwiched between the input and output layers. The obtained network is known as the Multiple Layer Perceptron (MLP). In each layer of this network there are some processing elements.

The used neural network is composed of an input layer (with three processing elements), a hidden layer (with two processing elements) and an output layer (with one processing elements). Processing elements in the input and output layers were listed in Table 3 and processing elements in hidden layer is compute by software.

To arrive from three inputs to a single output, various weights are given to the processing elements and an activation function is employed.

Therefore, all the elements of the hidden layer and finally the elements of the output layer can be computed. This is done for all input and output data sets. When all output was obtained, they were compared with their real values (measured) and the error value Root Mean Square of Error (RMSE) is computed from the following equation.

All the above said computation is performed using the Neural works software.

In this study, employing the above mention software and through selection of a MLP network, intervals of drains have been calculated. The number of processing elements in the inflow layer (the number of inflow variables) are the same variables required for computing the drain spacing by the Glover-Dummmethod which are p, k, d, h0, h, t. the output layer has one processing element which is the same drain space (L).

Data employed in the software using the Tables 1 and 2 are presented as Table 3. Data in Table 3 are as usable form in Neural works software.

These data were randomly divided into three parts and are used for training, testing and validation stages. Drainage is investigating in the domain since earliest periods to decrease the soil water and rise the efficiency of yields. The precise project of the organization can support the sustainability of the situation and decreases the adverse of over drain of the earths.

Table 1: Study area characteristics

Characteristics Part	Drain spacing (m)	Area (ha)	Distance between drain to the impermeable layer (m)	Effective porosity	Depth (m)	Hydraulic conductivity (m/day)	Drainage radius (m)	Drainage tube type
A	80	5.50	3.40	0.13	2	1.55	0.063	Flexible plastic
B	60	2.75	3.15	0.13	2	1.53	0.063	Flexible plastic
C	40	2.75	3.10	0.14	2	1.70	0.063	Flexible plastic

Table 2: The maximum and minimum water levels subside during the three consecutive irrigations in parts A, B, C

	Part A			Part B			Part C		
	First irrigation	Second irrigation	Third irrigation	First irrigation	Second irrigation	Third irrigation	First irrigation	Second irrigation	Third irrigation
$h_0(m)$	1.78	1.81	1/87	1.43	1.29	1.31	1.16	1.09	1.10
$h(m)$	0.60	0.71	0.73	0.30	0.26	0.46	0.13	0.28	0.34
$T(day)$	13.00	18.00	17.00	13.00	16.00	16.00	15.00	12.00	16.00

Table 3: Using neural networks application data

Process element in the output layer	Process elements in the input layer					
$L(m)$	$T(day)$	$h(m)$	$h(m)$	$d(m)$	$k(m/day)$	p
80	13	0.6	1.78	3.4	1.55	0.13
80	18	0.71	1.81	3.4	1.55	0.13
80	17	0.75	1.87	3.4	1.55	0.13
60	13	0.30	1.43	3.15	1.53	0.13
60	16	0.26	1.29	3.15	1.53	0.13
60	16	0.46	1.31	3.15	1.53	0.13
40	15	0.13	1.16	3.10	1.70	0.14
40	12	0.28	1.09	3.10	1.70	0.14
40	16	0.34	1.10	3.10	1.70	0.14

Artificial Neural Network (ANN) was applied to evaluate the drain spacing for unsteady. The advanced prototype was qualified and verified applying consequences attained from hypothetical and laboratory information. Numerous topologies with dissimilar involvement purposes, hidden layers, quantity of neurons have been verified and the finest topology was designated as best prototypical. Furthermore, the aptitude of prototypical in approximating the drain spacing was revealed applying field information. Overall, technique could calculate the drain spacing with related accurateness and together can be applied efficiently in field of agronomic drainage. The usage of Artificial Neural Networks (ANN) was examined as a different technique to attain results to the Boussinesq equality. Results were attained with a numerical technique, each one conforming to a single set of component standards. This finest ANN was exposed to diverse exercise administrations in order to regulate the most suitable one, the organizations containing of numerous numbers of exercise with the knowledge conventional. Presentation of the ANN at the numerous preparation stages was assessed and the optimum organization defined. It was defined the use of Artificial Neural Networks (ANNs) to prototypical the presentation of a subsurface drainage organization in Iran. The ANN prototypical was constructed and qualified by applying dignified information on water-table complexities and drain discharges. The consequences attained by the ANN prototypical were contrasted with the dignified information and the simulated consequences from a predictable accurate prototypical. The consequences display that the ANN prototypical can pretend water-table variations and drain discharges reasonably fine. The ANN prototypical performs meaningfully earlier and needs meaningfully less contributions. The ANN reproductions be contingent deeply on the superiority of the input information for together mediocre and great situations. It was designated that an ANN prototypical may be applied efficiently for the project and assessment of subsurface drainage organizations. The profits of ANNs are rapidity, correctness and suppleness. Artificial Neural Networks (ANNs) may show to be valuable in these circumstances. From side to side the preparation procedure, ANNs adjust weights in the interconnections between every couple of dispensation features (PEs) to decrease the alteration between preferred productions and present pretend consequences. ANNs can simply prototypical the association between input and output components in an implied technique, even while the issue is extremely non-linear.

Furthermore, they need meaningfully less input components than like predictable prototypes. Similarly, depend on this implied input/output association with equivalent dispensation through the internal constructions of the system, ANNs can perform reproductions very rapidly. The fast performance of ANNs benefits get forecasts for great-scale models. In new periods, ANNs have established many effective presentations in agronomy, it was constructed an ANN prototypical. It was used ANNs for the model of bully presentation. It was qualified ANNs to assess and forecast the superiority of nourishments. It was advanced visual irrigation organization for chicken feed depend on ANNs. It was applied ANNs to pretend water preservation arches on sandy dusts. The foremost purpose of this education was to progress an ANN prototypical for the mockup of water-table depths and drain discharges in a subsurface drained pastures of Ahwaz, Iran. The association amongst inputs, i.e., precipitation, evapotranspiration and preceding water-table depths and drain discharges and yields was pretend under kinds of drain spacing. The prototypical presentation was assessed by contrasting pretend standards with dignified information. Furthermore, simulated principles were contrasted with consequences gained by applying an ANNs prototypical.

The hyperbolic curve transmission purpose is calculated as subsequent:

$$Y = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$

where, Y is the yield of the dispensation features and X is the summed input indicator in every dispensation features. ANNs were verified at unsteady intermissions, the system was protected while consequences had enhanced contrasted to the previous organizations. So as to avoid the above-preparation of ANNs, this method was applied through the plan. Drain spacing, daily rainfall, daily evapotranspiration, water-table depth on the previous day and drain outflow on the previous day are the main components of ANNs. Whereas organization ANNs after exercise, evidence on everyday water-table and channel discharge variations rise to the daytime of reproduction is recognized and applied to mark the one-stage reproduction. The prototypical permits for simulation at a period. The experiential standards on the present stage developed inputs for the reproduction on the following stage.

Different standards were applied for prototypical assessment: Root-Mean-Square error (RMS), Standard Deviation of errors (SD) and the coefficient of determination (r^2). The consequences of r^2 were

gained from a database. The RMS and SD were designed as:

$$RMS = \sqrt{\frac{\sum_1^N \left(RO_n - RA_n \right)^2}{N}}$$

$$SD = \sqrt{\frac{\sum_1^N \left(R_{on} - RA_n \right)^2 - \frac{\left(\sum_1^N R_{on} - RA_n \right)^2}{N}}{N-1}}$$

Where:
RO = The observed value
RA = The simulated value
n = The record on each day
N = The total number of records

Respectable consequences with little faults and great covenant to dignified standards are offered by RMS and SD standards near to zero and by r^2 standards near to one. It is obvious from the information that ANN prototypes completed improved in forecasting component standards in practically all circumstances, RMS, SD and f standards are significantly improved for ANN models. The consequence is exact hopeful since ANNs is a materially-depend prototypical and needs a large number of soil systemic and meteorological components for its models. Also, the ANN mockups need moderately less input components and appear to have demonstrated consequences rather precisely. Also the climatological inputs, which are similarly compulsory by ANNs needs many components: Drainage plan, soil features, hydraulic conductivity, trafficability, land cover, etc. Meanwhile conservative reproductions requisite to have formerly distinct this complex association, construction ANN prototypes develops informal than evolving conservative prototypes to get consistently precise reproductions of water-table complexities and drain discharges (Yang *et al.*, 2013). Soil drainable penetrability (f) is definite as the capacity of aquatic that is drained through an item capacity of soil while the water table descents above a component space. The assessment of f is not usually persistent then also additional possessions, it is a purpose of water table penetration i.e., soil depth, Z. The period of form of the water table be contingent on the specific method in drainable penetrability is connected to water table deepness. It is suitable and frequently essential in educations to direct f as a purpose of Z. The f standards consistent to dissimilar Z were defined from water table or hydraulic head (h) and drain discharge (q) capacities. A useful association amongst f and Z was formerly advanced by reversion which is revealed and is defined by the subsequent calculation:

$$F = aZ^b \tag{1}$$

Somewhere 'a' and 'b' are the reversion constants. A mediocre assessment of f demonstrating the complete drainage current district can be gained by participating Equation (1) inside the border circumstances $Z = 0$ to Y and then separating by drain depth Y. Therefore:

$$f_{ave} = \frac{\int_0^Y aZ^b dz}{Y} = \frac{aY^{b+1}}{Y} = \frac{aY^b}{(b+1)} \tag{2}$$

Soil hydraulic conductivity (K) is the drainage water current per component zone of the soil form per component hydraulic slope. Approximating f, K correspondingly displays longitudinal difference. Consequently, it is similarly significant to include the inconsistency of K in drainage project calculations. For defining K conforming to dissimilar Z standards, K/f proportions were principal defined applying the process assumed and formerly this were increased by f standards attained from Equation (1). K standards so gained were planned in contradiction of Z standards. The subsequent relative was established:

$$K = \alpha Z^\beta$$

where, α and β are reversion coefficients.
A mediocre assessment of K can similarly be defined in a related way as applied for f_{ave}. Consequently:

$$K_{ave} = \frac{\alpha Z^\beta}{(\beta+1)}$$

The water table downturn throughout drainage of a soil outline is the measured central between drains, hereafter the most serious. If the water table is expected to be level, the degree of reduction of water table is unchanging amongst drains. Consequently, a steady formal drainage association, which similarly accepts an unchanging fluidity, can be applied to define the degree of reduction (dh/dt) of the water table amongst drains. Conversely with a dropping water table, the fluidity in overall differs with space from the drains. Henceforth so as to apply steady state explanations, an alteration factor C wants to be presented. Figure 1 shows Alteration of drainable porosity with water table profundity. The trend dramatically increases and R2 equals 0.955. Figure 2 shows Alteration of hydraulic conductivity with water table infiltration and the trend decreases and R2 equals 0.988. The appearance for drain discharge or drainage fluidity can be conveyed as:
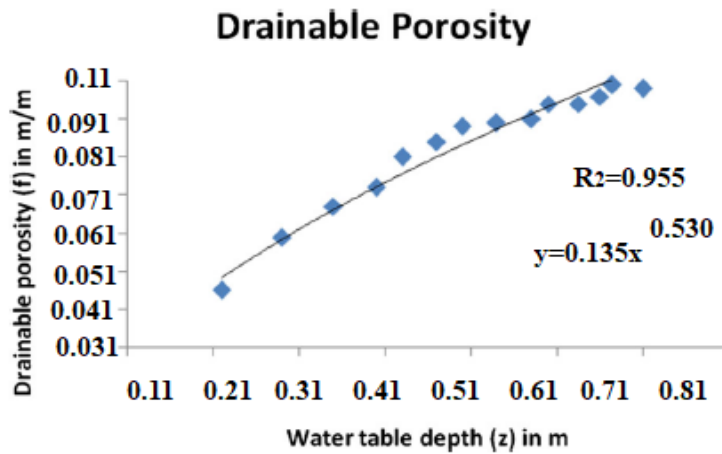
$$q = -fc\frac{dh}{dt}$$

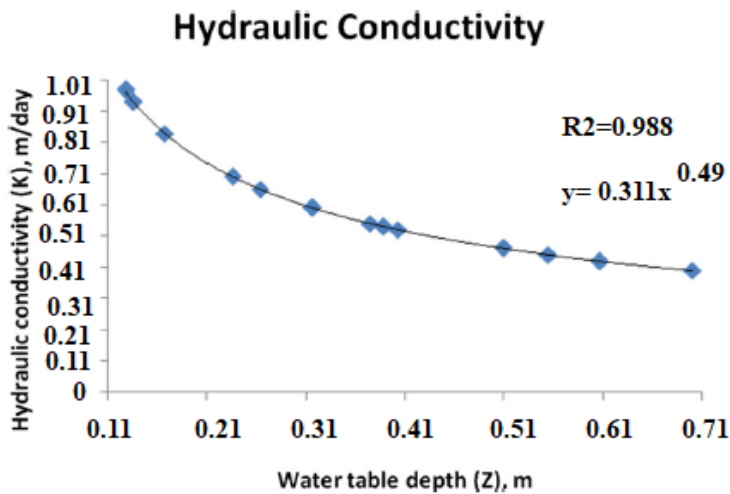**Fig. 1:** Difference of drainable absorbency with water table deepness

Fig. 2: Difference of hydraulic conductivity with water table penetration

q = drain discharge, mday^{-1}; f = drainable absorbency of the soil, in element. Undesirable symbol designates that h declines with rise in time, t. For increasing water table, adverse symbol fades. Here, h_0 is first assessment of hydraulic head and S is the drain spacing. It was measured the drainable porosity, f as persistent. But it has been recognized that f differs with Z. Meanwhile $Z =$ ($Y-h$), somewhere Y is the deepness of drain from ground superficial, It can be conveyed in relationships of hydraulic head, h as (Pali *et al*., 2014):

$$f = a(Y - h)^b$$

$$q = -aC(Y - h)^b \frac{dh}{dt}$$

$$h = \frac{qS}{K} F_D$$

$$F_D = \frac{1}{4} \left[\frac{S}{2D} - \frac{2}{\pi} \ln \left(2\cosh \frac{\pi r}{D} - 2 \right) \right]$$

$$F_D = \frac{1}{4} \left(\frac{S}{2D} - \gamma \right)$$

Results

The precise approximation of subsurface drain spacing under unsteady water table regime shows an important part in drainage project and is essential for the effect assessment of the current subsurface drainage organization in relationships of dropping of water table or for the control of components of innovative drainage organizations. The global drainage nonfiction predicts many calculations for unsteady formal organization with numerous grades of difficulty. Some of these calculations develop consecrated among investigators and originators complicated in drainage problems. The

inconsistency of the soil systemic possessions specially hydraulic conductivity and drainable porosity is the aim that numerous of these drainage project calculations do not do in conformism to the real ground presentation consequences. Greatest unsteady state drainage calculations obtainable undertake persistent standards of drainable porosity and hydraulic conductivity. Data of Table 3 were entered into the software and a multiple layer neural network with 6 processing elements in the input layer and a processing element in the output layer were selected. The number of hidden layers and the number of their processing elements and the type of activation function were obtained through trial and error. These results are as an example for high ability of neural work in determining of drain spacing.

Such that, first computations were started for a hidden layer with a processing element and through increased number of processing elements in a hidden layer and the number of hidden layers, minimum error was obtained.

This was done for the three types of linear activation functions, hyperbolic and sigmoid tangents. Mean error using 0.1455, 0.092 and 0.0491 respectively. Therefore, finally the minimum error for the artificial neural network is obtained using a hidden layer (with four processing elements) and a linear activation function. The hidden layer with 4 processing elements has less error. Through employment of this network, values for drain spacing were computed results of which are presented in Table 4.

Regarding Table 4 it is observed that the difference between the computed drain spacing using the artificial neural networks and their real values is not statistically significant. In the meantime, the mean computed distance through the Glover-Dumm equation for the A, B and C sections are 53, 43 and 33 meters respectively indicating that their difference with the real values is considerable.

Such a difference is also seen for other computation formulas used for calculating drain spacing at the unsteady state. Therefore, it can be concluded that using artificial neural networks for determining the distance of drains at the unsteady state provides very desirables

results compared with other formulas (Shukla *et al.*, 1996; Thirumalaiah and Deo, 1998).

Discussion

Exactly all unsteady subsurface drainage calculations advanced thus far usage persistent price of drainable permeability and hydraulic conductivity that it was not characteristic of whole drainage current area. A drainage calculation was, therefore, advanced including deepness-sensible inconsistency of drainable permeability (f) and hydraulic conductivity (K) of salty earths of Ahvaz zone in Iran. The drain spacing with dignified hydraulic heads at dissimilar stages of drainage to be were assessed by the advanced calculation and contrasted with the consistent drain spacing assessed by usually applied unsteady drainage calculations. The facility of drainage particularly subsurface drainage is a significant method for regaining water recorded and saline soils. The instrument of this purpose is attained by subsurface drainage, includes the treatments of current of liquids through the soil outline and so be contingent deeply on soil drainage possessions. The operative project of subsurface drainage organization is categorized in expressions of soil drainage possessions, drainage organization components and border situations. The drainage project in moist zones usually is depend on the knowledge of a steady public organization and the project standards need the changeable of a quantified deepness of water to confirm satisfactory drying of the soil.

Conclusion

Many drainage employees have advanced unsteady public drainage models for moistened domains. Regularly Boussinesq calculation has been applied to comprehend unsteady water table variations in subsurface drainage difficulties. Greatest of unsteady state drainage calculations need drainable permeability (f) and saturated hydraulic conductivity (K) as soil possessions that straight impact the drainage procedure. The drainage calculations apply persistent standards of the possessions and may be valuable for drainage project in consistent earths but the earths are seldom come across in ordinary schemes.

Table 4: Comparison between calculated and actual values which drains

Part name	Irrigation	Calculated (m)	Calculated distance (m)	Realistic (m)
A	First	78.5	79.2	80
	Second	79.3		
	Third	79.9		
B	First	61.6	60.5	60
	Second	59.9		
	Third	59.9		
C	First	42.7	41.8	40
	Second	41.2		
	Third	41.6		

Usage of persistent standards of f and K in subsurface drainage project frequently clues to difference in hypothetically projected consequences and the investigational consequences. It is essential to include this heterogeneity in drainage project calculations. It was assumed for emerging an unsteady subsurface drainage calculation including inconsistency of drainable absorbency and hydraulic conductivity of the earth. The presentation consequences of the advanced calculation were similarly confirmed with the ground consequences.

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Author's Contributions

All authors contributed to design the study, write and revise the manuscript. sss

For Ethical Statement

The present study was approved by the Isfahan University of the Technology, Iran.

Ethical Approval

The present Study and ethical aspect was approved by the Isfahan University of the Technology, Iran.

Informed Consent

Research has flourished in the past few years with regulatory authorities, investigators and Ethics Committees striving toward conduct of quality and ethical with stringent regulations and updated guidelines.

References

French, M. N., Krajewski, W. F., & Cuykendall, R. R. (1992). Rainfall forecasting in space and time using a neural network. Journal of hydrology, 137(1-4), 1-31.

Golmohammadi, G., Salami, M., & Mohammadi, K. (2009). Estimation of drain spacing using artificial neural network and fuzzy logic. EGUGA, 495.

Häggblom, O., Salo, H., Turunen, M., Nurminen, J., Alakukku, L., Myllys, M., & Koivusalo, H. (2019). Impacts of supplementary drainage on the water balance of a poorly drained agricultural field. Agricultural Water Management, 223, 105568.

Jain, S. K., Das, A., & Srivastava, D. K. (1999). Application of ANN for reservoir inflow prediction and operation. Journal of water resources planning and management, 125(5), 263-271.

Kumar, M., Raghuwanshi, N. S., Singh, R., Wallender, W. W., & Pruitt, W. O. (2002). Estimating evapotranspiration using artificial neural network. Journal of Irrigation and Drainage Engineering, 128(4), 224-233.

Pali, A. K., Katre, P., & Khalkho, D. (2014). An unsteady subsurface drainage equation incorporating variability of soil drainage properties. Water resources management, 28(9), 2639-2653.

Qian, Y., Zhu, Y., Ye, M., Huang, J., & Wu, J. (2021) Experiment and numerical simulation for designing layout parameters of subsurface drainage pipes in arid agricultural areas. Agricultural Water Management, 243, 106455.

Rogers, L. L., & Dowla, F. U. (1994). Optimization of groundwater remediation using artificial neural networks with parallel solute transport modeling. Water Resources Research, 30(2), 457-481.

Shukla, M. B., Kok, R., Prasher, S. O., Clark, G., & Lacroix, R. (1996). Use of artificial neural networks in transient drainage design. Transactions of the ASAE, 39(1), 119-124.

Thirumalaiah, K., & Deo, M. C. (1998). River stage forecasting using artificial neural networks. Journal of Hydrologic Engineering, 3(1), 26-32.

Yang, C. C., Prasher, S. O., & Lacroix, R. (2013). Application of artificial neural network to land drainage engineering. Trans. ASAE, 39(2),525-533.